A Review on Applications of Electroencephalogram: Includes Imagined Speech

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***Abstract*—In the last two decades, the Brain-Computer Interface system with EEG signals has assisted people in various ways. In particular, to patients with paralysis, epilepsy, and Alzheimer's disease, not only to the patient but also to physically, visually challenged people and Hard-of-Hearing people. One of the non-invasive methods that can read human brain activities is Electroencephalogram (EEG). The EEG has been used in many applications, especially in medicine. The applications of the EEG are not limited to the medical domain; it keeps extending to many areas. This review includes the various application of EEG; and more in imagined speech. The main objective of this survey is to know about imagined speech, and perhaps to some extent, will be useful future direction in decoding imagined speech. Imagined speech classifications have used different models; the models are discussed, the significance of choosing the number of electrodes, and the main challenges in EEG.**

***Keywords*—Electroencephalogram; brain signals; invasive; non-invasive; imagined speech; electrodes; epilepsy**

I. Introduction

Speaking, hearing, seeing, and moving are all necessary to humans. However, few people are having issues with that, either by birth or due to illness. They could not lead an everyday life. However, technology and science can provide some alternatives for them. Artificial Intelligence (AI) and Brain-computer Interface (BCI) [1] are considerable gifts to them to lead a better life. The Brain-Computer interface system introduced during the year 1973 by Jacques Vidal. It converts the human brain signals into instructions for the computer [2].

In the last two decades, Brain-Computer Interface had a vital role in the field of the medical domain. In particular, for those who have paralyzed, have a seizure problem, have a brain disorder, have speech problems, have hard of hearing, and so on., it has given confidence to them in assisting in many ways. Specifically, they are not necessary to depend on others. A fully paralyzed person has motor issues, eyeballs that will not move, and articulation problems. They cannot communicate in any other technique except brain wave with the BCI system [3] because, cognitively, they are normal. Invasive and non-invasive methods are available to read brain signals. Many researchers have used these methods, but for the practical approach, non-invasive is more suitable rather than invasive. Complete details were in the other sections of this systematic review. Imagined speech, covert speech, inner speech, and intended speech are new paradigms for researchers. No phonetic sounds, but tongue and jaw movements will be present are refers as silent speech. Imagined speech is akin to silent speech, but tongue and jaw movements will not be present; a person should be in verbal thinking [4].

As per Proix et al., non-invasive methods have not given convincing results and have limited success due to brain signals taken on the scalp by either EEG or MEG technique during the imagined speech; brain signals are weak and vary with overt speech [5]. Instead of non-invasive, Proix et al. used invasive techniques. Many researchers have applied Machine learning or Deep learning algorithm to decode imagined speech using non-invasive.

The deep learning method required massive data to train the model for good accuracy [6]. This systematic review includes details of the few machines learning algorithm and the deep learning algorithm applied in decoding EEG signals by the researchers. Reddy et al. proposed Hamilton-Jacobi-Bellman (HJB) equation to get an optimal update rule for training Feed Forward Neural Network (FFNN); in this, the author achieved faster convergence and better performance [7].

In any BCI application, the brain signal controls the system. BCI system is composed of four different phases. Signal Acquisition, Feature extraction, classification, and device output [8]. Reading electrical activity of the brain is called signal acquisition. Different modalities are available to acquire the signals in the brain; EEG is one of the modalities. The details have given in the following section. Feature extraction is a method of analyzing the signal as per the application. Assign a label to the extracted feature in the classification result; this will enable specific control commands like cursor control, robotic arm movement, and user feedback. Thus, it closes the loop [8, 9]. Before performing all these, people must know about the human brain.

II. Brain Anatomy

The human brain has divided into two different portions: the cerebellum, a smaller portion, and the cerebral/cortex, a large portion of the brain. The brain's cortex area has divided into four different lobes: frontal lobe, parietal lobe, temporal lobe, and occipital lobe, respectively. Each lobe has its function. The frontal lobe is associated with cognitive function, speech, and short-term memory.

The responsibility of the parietal lobe is to have senses like smell, taste, and touch. The temporal lobe is associated with the hearing and memory process. The occipital lobe recognizes color and visual processes. Broca's and Wernicke's are associated with speech and language [10].

A. Brain Signals

The brain generates the electrical activity of the brain signals. During the electrical activity, electrochemical signals pass through the entire brain region with oscillation; they are called brain signals [11]. Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) are the five different brain signals generated in the human brain [12]. Details of brain signal's frequency and its associated characteristics are provided in Table I.

TABLE I. CHARACTERISTICS OF THE BRAIN WAVE

Frequency Band	Frequency in Hz	Brain states	Originating place
Delta (δ)	0.5 - 4	Sleep	Frontal lobe
Theta(θ)	4 -8	Deeply relaxed	Temporal lobe
Alpha(α)	8 - 12	Very relaxed, eyes are closed	Frontal lobe & Occipital lobe
Beta(β)	12 - 35	Active, high awareness, and eyes open	Frontal lobe & central
Gamma(γ)	Above 35	Full concentration	Frontal, Temporal, and Parietal Lobes

B. Brain Signals Acquisition

There are two methods in the signal acquisition, namely Invasive and non-invasive methods. The first method required surgery to implant the electrodes in the brain's cortical area. The second one does not require implanting. Moreover, for research and practical purpose, it uses the non-invasive method. Its ease of use, cost-effectiveness, better accuracy, and reliability with the advancement of technology is why it prefers the non-invasive method [13]. Invasive type of electrode requires surgery to implant. Electroencephalography (ECoG) should place on the brain surface under the skull. ECoG provides electrical potential measured directly on the brain surface at a high spatial and temporal resolution without filtering the signals through the skull or scalp [14]. Intracortical electrodes are inserted in the cerebral cortex to record electrical signals. Any invasive electrodes have high spatial and temporal resolutions with the drawback of neuronal damage [15, 16]. Electroencephalography (EEG) Hans Berger recorded his first EEG in 1924. It is a non-invasive type [17]. Traditionally EEG is considered low spatial resolution but good at a temporal resolution [18]. A few researchers proved that the EEG is good at spatial resolution using surface Laplacian computation [19] and Tripolar Concentric Ring Electrodes [20] and combining EEG and fMRI to encode visual stimuli [21]. Magnetoencephalography (MEG) measures brain activity by the magnetic field generated by the electrical activity of the neurons. It provides high spatial and temporal resolution than the EEG [22, 23].

Functional Magnetic Imaging (fMRI) Clinical laboratories use Functional Magnetic Resonance Imaging (fMRI). When a particular brain area is active, that area will have more blood flow. fMRI finds the activity of the brain during changes in blood flow. The fMRI is good at spatial resolution and poor at a temporal resolution [24, 25]. Functional Near-infrared Spectroscopy (fNIRS) is a non-invasive brain signal acquisition device. Which is used widely in clinical applications like Parkinson's, Alzheimer's diseases, and childhood disorders could be diagnosed, and also it could be used in the Brain-computer interface. It emits less radiation, is user-friendly, has less cost, and is portable [26].

Among all non-invasive methods, EEG is the better option for researchers. Because of these reasons, easy to use, cost-effective, portable, and good at temporal resolution. In general, spatial resolution is low. However, it could enhance with Surface Laplacian computation [19] and Tripolar Concentric Ring electrodes [20] and more use of practical applications. 1 to 256 channels are available.

C. International Standard 10-20 EEG System

EEG signals are non-linear and highly non-static. The numbers 10 and 20 are the distance between adjacent electrodes. 10% and 20% of the total distance of the skull from the front to the back or left to right [26, 27]. Reference points of the measurements are Nasion (which is between nose and forehead), Inion (which is the lower point of the skull), vertex (which is the center point on the top of the skull), and pre-auricular points anterior to the ear. Moreover, F, T, O, and P denote the Frontal Lobe, Temporal Lobe, Occipital Lobe, and Parietal Lobe of the brain area. Sub-indexes indicate even or odd numbers for the right and left hemispheres [28].

Researchers are using three kinds of evoked potential to measure the electrical activity of the brain. Three kinds of evoked potentials are used to measure the human brain's neuron activity during a stimulus and response. They are:

Auditory Evoked Potential [29], Visual Evoked Potential [30], and Somatosensory Evoked Potential [31], respectively. In his 2017 study, Spüler wrote that Visual Evoked Potential (VEP) has significant communication speed in non-invasive EEG. To read an electrical signal from the brain gel-based electrode or dry electrode could be used. The application of gel-based electrodes takes more time to capture the signal. In order to create a more user-friendly BCI system, we can use dry EEG electrodes with a VEP-based system. However, it gives high variability between the subjects. Introduces averaging and dynamic stopping methods to mitigate the performance variability and deal with the lower signal-to-noise ratio of dry electrodes [32].

III. PREVIOUS WORKS IN EEG

Though the invasive method is sound in SNR and spatial resolution and apt to the BCI application, the risk factor is possible after the surgery [33]. Therefore, researchers are choosing the non-invasive method. The medical domain uses EEG for early identification of Alzheimer's, Parkinson, Paralyzing, and Epilepsy, and monitoring Anesthesia drug levels during surgery. Few researchers are also showing more interest in the non-medical domain, like decoding covert speech; this will be useful to impaired people, even brain-id for authentication purposes, Emotion detections, and in-home appliances.

The EEG signals have been used in many applications related to brain wave analysis, like the presence of epilepsy, to classify the covert word, brain-computer interface to activate external devices, and Emotion detection.

A. EEG Applications in Diagnosing Brain Disorders

1) Epilepsy: Conventionally neurologists go for a direct visual method to predict the epileptic abnormality. However, it takes more time to predict, may produce a variable result, and abnormality has limitations. Nowadays, to predict the above abnormality, a Computer-Aided Diagnosis is used [34]. In their work no separate steps for feature extraction and feature selection because they used the deep CNN model; this is one of the models in the deep learning technique [35]. The model will help predict Seizure disease. However, the data set was not enough for excellent performance, and the data should increase or apply data augmentation method [36] to achieve optimal performance of the result.

In another research, the author compared various Ensemble methods like bagging, boosting, Ada boosting, Multi boosting, random subspace, and rotation forest to discriminate the non-epileptogenic region of the brain with the epileptogenic location of the brain. They concluded that the rotation forest classifier had high performance [37].

2) Parkinson's disease: Many Parkinson's patients have a problem with locomotion. They will get stuck in forwarding movement while walking due to the Freezing of Gait (FOG) issue. One study revealed that it is possible to predict the FOG of Parkinson's disease (PD) before happening through EEG visual or auditory cues. The author investigated the specific EEG feature to implement real-time FOG prediction [38]. They used three layers-back propagation neural network model. They achieved 85.86% of sensitivity and a specificity of 80.25%.

B. EEG Applications in Emotions Detection

Emotions are the real feelings of humans, and the human brain controls them. Every human can have positive and negative emotions [39]. Positive emotions are love, happiness, surprise, joy, etc., as negative emotions are guilt, sadness, and annoyance. In various situations, they generate these emotions. If the emotions are within a limit, no problem for humans, or it may affect their health. Early identification of these problematic emotions makes it possible to reduce the many problems. Initially, the researchers detected these emotions using facial expressions, Text, or gestures [40]. They developed a model to recognize their facial expression or their gestures. However, nowadays, researchers are interested in using the human brain with the help of EEG. Much research has been available to classify emotions in the last decade. One study concluded that the neurons in the left hemisphere are active during positive emotions, and those in the right hemisphere are active during negative emotions [41].

C. EEG Application in BCI

One of the main aims of the BCI is to assist the paralyzed person in communicating with the outside world by controlling assistive devices through their brain signals without moving their legs or hands so that the dysfunctional motor system can bypass them. Some neuronal disorders cause patients to suffer significantly from impaired communication, including amyotrophic lateral sclerosis (ALS). As per the study by Chaudhary and his team in 2001, paralyzed patients could communicate with the aid of multiple brain-computer interfaces (BCI), including those that use electroencephalography [42].

P300 speller is one of the most popular BCI applications. There is a possibility to increase the performance of the P300 in practical usage. The author has examined the correlation between the P300 speller's versions with Rapid Serial Visual Presentation (RSVP) task features in this paper. In this study, the author identified the features of the correlation between the ERP (Event Relation Potential) and its behavior in offline binary classification accuracy. Using these features, the author proposed a simple multi-feature predictor. Their study revealed that a multi-feature predictor model could achieve higher predictability than the single-feature predictor model [43].

A recent study shows that a new system dimension controls the categories of people with speech problems and with ordinary people to assist them in everyday life by humming [44]. This article revealed the feasibility of EEG in BCI with vocal Imagery and vocal Intention. Four types of tasks were instructed to the subjects to perform, non-task specific (NTS), motor task (MT), vocal Imagery task (Vim), and vocal Intention task (VInt). The author concluded that the Vim task was highly classifiable in the EEG paradigm with BCI systems.

In their 2019 study, Kim et al. believe that the application of Brain-Computer Interface has been reaching out to non-medical applications too. That controls home appliances like a TV, digital door-lock, and electric light [45]. In another research, the author developed an assistive BCI system, which is helpful to differently-abled people. It will generate synthesized speech while the eye is blinking. During EEG recording, when the subjects notice the desired option on the display, they will wink their eyes; the system generates the synthesized speech per the options display. This system will be helpful to a patient who has a locomotive disorder like "locked-in syndrome"; this patient can communicate with their caretaker. This model could be used only for patients who have neurology disorders. Here the author suggested that instead of eyeblink EEG signals better to identify imagined movements through EEG signals [46].

D. EEG in Authentication

In information security, authentication is essential for in-person identification. Many techniques exist, like hand signature, password, fingerprint, iris, face, and voice recognition. However, all these have vulnerabilities. There is an alternative technique for every authentication technique, like forgery in the hand signature; the password can hack, film for fingerprint, contact lenses for the iris, face masks, and a voice vocoder [47]. Brain signature is the best solution because it is unique and cannot steal or hack. In one study, the author used only Alpha and Beta waves captured through EEG while subjects read 4-digit numbers when they saw numbers. A linear Discriminant algorithm (LDA) have used in the classifier. The training model has taken Common Spatial Analysis (CSA) values. Before authenticating, the trained model should have all the user's details. Finally trained model is used to authenticate the user [48]. In the later study, the author found that the delta wave has more specific information in user identification among all the five brain waves [47].

This research used biometric authentication to identify the individual using the brain signal system. The author captures EEG signals while performing three mental tasks with the participants. The author adapted a novel protocol and algorithm using NN and used mu and beta waves with a single trial analysis to test the novel algorithm. The Levenberg Marquardt back propagation algorithm trained NN. This research shows that the reading task is more suitable for biometric verification [49].

E. EEG in Imagined Speech

In the world, approximately nine billion people have problems speaking and hearing either by birth or accidentally last their speaking and hearing capability. It is tough for them to speak with ordinary people. With the same community, they can communicate with their sign language. (Communication between visually challenged and ordinary people is acceptable since they can speak well). Many researchers have developed an assistive tool that helps hard-of-hearing people communicate with ordinary people by converting sign language images into audible speech.

Recently researchers are showing interest in decoding the intended speech using brain waves invasively or non-invasively. In the last year, a few scientists have proven that imaged speech can interpret by implanting electrodes invasively using AI in the medical domain.

Imagined speech or covert speech, or inner speech, is a new paradigm used in the Brain-Computer interface to assist impaired people in communicating with the outside world for those who cannot produce the speech either partially or entirely or due to any health issues. Imagined or covert speech means thinking of a word without having articulation sound or tongue movement. An Imagined word could capture in EEG.

Since the last decade, researchers have been involved in imagined speech using EEG brain signals. Decoding silent speech will be helpful in many aspects like locked-in syndrome people, cognitive biometrics, and entertainment [50]. All the researchers used a complete band frequency with the different channels and subjects. However, Valuable information may not be present in the EEG signal during the analysis period <100ms. Better decoding accuracy in the classification, especially in the phase pattern in Theta and Delta waves [21].

This systematic review contains the classification performance result of the model. The researchers used the subjects to imagine the different vowels, consonants, words, both the vowel and words, and directions in symbols or words and objects. They used different classification algorithms. Most researchers applied benchmark algorithms like SVM, Random Forest, and LDA.

Methodologies used in imagined speech classification: Support Vector Machine (SVM) has been used in EEG classification for the diagnosis of neurological disorders [51]. This model was used effectively in many applications for disease prediction analysis, particularly in the medical domain. The linear SVM is an efficient technique for high-dimensional data application. Nowadays, researchers have used EEG brain signals to decode imagined speech. Support Vector Machine (SVM) is used in imagined speech analysis using EEG signals. The following article has evidence of the application of SVM to classify vowels and consonants [21, 52, 53]. To classify the Imagined word [50]. In one more repeated study, SVM as a benchmark algorithm is used to classify the vowels [54].

Extreme Learning Machine (ELM) is another effective classifier. Many real-time applications use the ELM technique. It is for binary as well as multi-class classification. It has a high learning speed, so researchers have used this model in robotic applications [55]. Since its fast-learning capability and no iteration, the reason is that a single hidden layer connects the output layer; it is used in EEG applications to classify the imagined vowels and words [53, 56]. The performance of ELM in sparse high-dimensional applications which are currently under investigation [57].

In Decision Tree (DT), only training data is sufficient because once the decision tree is present with the help of training data, it can support new samples. While classification, new data was inserted without disturbing the entire tree. Moreover, it is very flexible to include the sample [58].

The importance of channel selections and reducing electrodes are in the next section. For these, the decision tree algorithm is suitable because EEG signals may contaminate with noises or contain irrelevant information, which will reduce the classification's performance. One study revealed that a decision tree could improve performance.

Furthermore, the authors proved that the decision tree is better than the following algorithms: Mutual information, SVM, CSP coefficient, and Fisher's criterion, respectively [59]. It is easy to interpret the brain signal by a decision tree. However, if the data set is large, then it is challenging. For smaller data decision tree is more suitable for decoding silent speech [50, 60].

Random Forest (RF) is another classifier. Recent study proved that sufficient electrodes could reduce the time and effort in analysis during EEG signal classification by the time Random Forest model [61]. The random forest model is an improved version of the decision tree, widely used in EEG signals classification. The Random Forest model is used as a benchmark classifier to classify vowels and words [54] and in the imagined word classification[50].

Linear discriminant analysis (LDA) is a familiar feature reduction technique to project the features in higher dimension space into lower dimension space. Moreover, as a classifier, it is used. It creates a new axis from the features, reducing the variance and increasing the two variables' class distance. The main drawback of LDA in feature reduction is required all the features as the input signal. The new feature is calculated based on all the observations. This situation will not occur in real-time BCI applications [62].

K-Nearest Neighbor (KNN) is a multi-class classifier. It does not take training duration; the reason is that the data itself is a model. Implementation is straightforward when compared with another classification algorithm. The reason is that it just calculates the distance between the different features using either Euclidian or Manhattan**.** Moreover, it has only one hyper-parameter k and several clusters. However, it has a few drawbacks also.

For small datasets, it works well, but not in large datasets and high dimensional data sets. It also takes more cost to calculate the distance. Noise and missing data can affect this model. In the imagined word classification, Naïve Bayesian and MLP models are used [50, 63].

Classifying the EEG signal with a few layers in CNN is impossible. For better classification accuracy Deep Neural Network could be the best for the EEG imagined data [64]. CNN[54, 64, 65] RNN and DBN[66], DNN[67]. The DBN was introduced in 2006 and, in the next year, was analyzed by Bengio [68]. The table shows the pros and cons of the various classifier.

1) Subject focused on imagine vowel and consonant: Table II depicts various studies involved in classifying imagined speech with vowel and consonant using different model. One study shows the discrimination between the vowel sound of /a/, /u/, and rest as control states for the imagined. The vowel /a/ and /u/ was the following muscles involved while uttering these vowels. They are digastric and Orbicularis Oris muscles [52]. They used a linear classifier and SVM to give the excellent performance result in the table.

TABLE II. IMAGINE VOWELS AND CONSONANTS

Reference	Vowels/ Consonant	Classifier	Performance
[21]	/a/, /e/, /i/, /o/, /t/	SVM	δ, θ has better classification accuracy in the phase pattern
[52]	/a/, /u/, rest	Linear, SVM	87.5 – 100% 78.33 – 96.67
[53]	/a/,/e/,/i/, /o/, /u/	ELM	68.5%
[65]	/a/,/e/,/i/, /o/, /u	CNNeeg1-1 Compared with DL Shallow CNN	65.62% in BD1 and 85.66% in BD2

In another study, the vowels /a/, /u/, / i/, /o/, and /u/ were used. They aimed to classify the imagined speech of EEG using a single trial [53].

In the Feed-Forwarded Neural Network [6], all the weights and biases are necessary to tune each layer. It slows down the process. Therefore, the author used the ELM method. G. Huang invented ELM [53, 57], which uses random weight to calculate output weight analytically. Hence learning speed is significantly high compared with other conventional neural network algorithms.

Normally classifying EEG data gives poor generalization overfitting due to limited samples. However, the generalization was good in this research and achieved minimum squared training error. The result shows that the ELM and its variants have better classification results than other algorithms [53].

One more research conducted used all the vowels /a/, /u/, /i/, /o/, /u/ and created a new dataset with 50 subjects. In this, they proposed a new algorithm named CNNeeg1-1 in deep learning to classify imagined vowels in EEG signals and compared the performance of CNNeeg1-1 with DL Shallow CNN and EEGNet benchmark algorithm by an open-access dataset (BD1) and a new dataset (BD2). CNNeeg1-1 performs better than the other mentioned algorithm, with 65.62% in BD1 and 85.66% in BD2 [65].

Another study used English alphabets /a/, /e/, /i/, /and /t/ they identified that the EEG phase signals have more information than the other frequency band of the EEG signal during auditory and visual stimuli. So decoding accuracy is more in EEG phase signals than the power information.

Also, it is possible to get good accuracy in decoding during the time between 180ms and 300ms after the appearance of the stimulus [21].

Subject focused on imagine words: Table III shows that some of the researchers used specific words instead of using either vowels or consonants. So that the model will be helpful to persons who are not able to speak or not able to move their bodies; they could get help from the caretaker.

TABLE III. IMAGINED WORDS

Reference	Words	Classifier	Performance
[10]	Go, back, left, right, stop	ELM	40.30% and 87.90% in multi-class and binary class
[50]	Sos, medicine, stop	RF, DT, KNN, SVM	76.4% in theta wave.
[63]	Yes, no, the rest state	MLP	Yes vs. rest 73.73% No vs. rest 75.38% Ternary classification 53.91%
[66]	10 CVC	RNN, DBN	72% & 80%
[67]	In, Cooperate	DNN	71.8 %
[69]	Forward, backward, up, down, help, take, stop, release	ResNet18+2GRU	85%
[70	Ambulance, hello, light, stop, toilet, water, clock, help me, pain, thank you, TV, and Yes.	RF, SVM	39.73±5.64% in imagined speech. 40.14±4.17% in visual imagery.

It is possible to develop more intuitive BCIs for communication-based on BCI activation tasks involving covert speech. The author used 'Yes' and 'no' as imagined words [63]. In the same year, Quresh et al. conducted more research to classify the five words: go, back, left, right, and stop. They used a sigmoid activation function-based linear ELM classifier and all the frequency bands. The author suggested that δ and α can be used instead of all the frequencies. Because more activation processes were present in that frequency band [10], they achieved good classification results in both the multi-class and binary classification.

In another research, the author suggested that acquiring EEG signals from more channels will increase the training data size. It improves the classification accuracy in the deep learning technique [67]. Furthermore, channel selection also has a vital role [18]. It is easier to train a DNN if the selected channels correspond to individual imagined words and are considered independent data vectors [67]. This author has taken two words to decode one short word, 'in' and one long word, Cooperate, and the DNN model gave a 71.8% performance result. A large data set is required to build a neural network classifier for good accuracy. In another paper, Vorontsova confirmed that a small data set is enough to construct a more accurate neural network classifier on EEG in a single participant subject rather than a group of subjects with an extensive data set. In addition, they concluded that limited sample EEG data could apply to the general population [69]. In silent EEG, speech recognition with Russian words: Forward, backward, up, down, help, take, stop, release, and pseudo-word. The research conduct result shows that RNN yields good accuracy than CNN.

To identify the vowel from Consonant-Vowel-Consonant words were used RNN and DBN models. From the brain connectivity estimator result, the author identified that more electrons are activated during speech and imagery speech in the left frontal and left temporal portions. Deep Belief Network has given a better classification result than the RNN [66].

A recent study by Agarwal & Kumar (2021) analyzed all the brain waves of the three words of silent speech sos, medicine, and stop. The research result was 76.4% accuracy in the theta wave. This research identified that more details would be available in theta and high gamma waves during a silent speech [50]. Moreover, some words share a similar pattern in brain activity [69]. Decoding EEG signals with more classes is also not advisable. In multi-class classification, the author found that the decoding performance may reduce moderately due to the more feature in imagined and visual imagery speech while decoding imagined words [70].

TABLE IV. IMAGINE VOWELS AND WORDS

Reference	Vowels/Words	Classifier	Performance
[54]	/a/, /e/, /i/, /o/, /u/ up, down, left, right, backward, forward	CNN	Word accuracy 24.97% Vowel accuracy 30%
[64]	/a/, /e/, /i/, /o/, /u/ up, down, left, right, backward, forward	CNN, TL	CNN-23.98% and 24.77%, 24.12%, 23.22%

2) Subject focused on imagine vowels and words-repeated study: Table IV depicts two research conducts have done the repeated study with the same open-access data set created by Coretto but used a different method to classify the word [54, 64]. The article's main objective was to enhance the classification result by decoding imagined speech in EEG using DL with Hyper-parameter optimization [54,71] on classifier performance. They tried both overt and covert speech. From this, the author concluded that CNN has significantly better accuracy than SVM, RF, and rLDA classifiers. All the classifiers used the nCV method for HP optimization. The result shows that the robust selection of HP in CNN for decoding was critical. The effect of the model determines by the number of epochs, activation function, and learning rate. So, the selection of optimal HP depends on the other hyper-parameters [54]. The author proposed a new CNN for the classification in the subsequent repetition study. The idea was to reduce the complexity, retaining the same accuracy, but the result has shown considerably less accuracy. The author recommended more data and powerful machine learning algorithms to increase accuracy. The effectiveness of the neural network improved through transfer learning [72].

The research revealed that the brain signal is unique for the same imagined action in a different subject [64]. Subject focused on imagine directions: Feature extraction and classification have a vital role in any BCI system. Researchers have used classical approaches like pattern recognition in feature extraction and classification for decades. Now many researchers are applying a deep learning approach in many areas. Few researchers have introduced the deep learning method into the study of biomedical signals, especially EEG signals. Table V shows that the subjects were imagined the directions instead of vowel, consonant, or words.

TABLE V. IMAGINE DIRECTIONS

Reference	Direction	Classifier	Performance
[56]	Left, right, up, and down	ELM multi & binary	49.77%
[73]	+, ← or → Both feet and tongue	CNN	92.7%

In their research, input has been taken based on wavelet transform; the time-frequency input images acquired in the C4, C3, and Cz channels; resize technique is applied to the input image to minimize the training duration in 2D CNN. The research result shows that the proposed method is more efficient in the 1D kernel with fewer parameters. However, it has challenges in performance due to the quality of the signals and limited samples [73]. Another research proposed by Pawar & Dhage (2020) in multi-class covert speech classification using an extreme learning machine (ELM). The ELM provides the generalized and optimal solution in multi-class covert speech recognition. It has the advantage of training and testing the model will take less cost because it is a single hidden layer feed-forward neural network. It is not required to tune the weights. Moreover, the author has shown that the EEG signals taken from a particular region in the brain will be sufficient instead of acquiring signals from the entire brain. Their future challenge is to develop an intelligent algorithm to classify many words in real-time [56]. The authors have taken three different brain areas; Brain Area 1 was the Prefrontal cortex, right inferior frontal gyrus, and Wernicke's and Broca's areas. Brain Area 2 is the same as Brain Area 1, and Brain Area 3 is the entire brain area.

3) Subject focused on imagined object: Table VI shows that the objects were used instead of imagine vowel, consonant and word.

TABLE VI. IMAGINED OBJECT

Reference	Objects	Classifier	Performance
[60]	Cube, Rectangular prism, Pyramid	Decision tree	43%

The author used two visually challenged subjects and two sighted subjects to recognize the objects. The author achieved 43% classification accuracy, which was less. Still, it could be 90% accurate for an enormous decision tree, but if it is too large, it is not easy to analyze. The author revealed that sighted people could identify the object through their vision signal though blindfolded. It means the occipital lobe was significantly active. However, visually impaired people identified the same things by sensing only. Neurons in the parietal lobe were active [60].

However, this decoding of covert speech is in the NP-Hard problem only; we hope it will soon be NP-Complete. If researchers achieved 100% success in decoding covert speech and deploying it successfully, many impaired people could lead better life in society.

IV. SIGNIFICANCE OF THE NUMBER OF CHANNELS AND SUBJECTS, KEY CHALLENGES

It is essential to select the proper electrodes and their locations. If fewer electrodes are selected correctly, they may retain critical information. If too many electrodes are selected, then it may produce redundant information. Similarly, the number of subjects is essential to acquire the EEG signals for better classification results. Training a model with significantly fewer data will be an issue with underfitting. Sometimes an over-fit problem may occur after training a model with sufficient data. So, it is necessary to have more subjects and attention to place sufficient electrodes in the scalp location as per the researchers' application. In one research, the authors stated that increasing the number of electrodes in the front temporal of the brain's left hemisphere could improve the imagined speech signal reorganization [65].

Many researchers showed more interest in decoding imagined speech using the non-invasive method. Various techniques were used to increase the accuracy of the classifications; however, it is hard to implement in a real-world scenario. Because of an insufficient EEG data set, takes long calibration time, Poor SNR and non-static signal. These are all significant challenges to the researchers.

V. CONCLUSION

In this systematic review, number of studies reviewed, which reveals a promising result for decoding imagined speech using vowels, consonants, words, directions and objects from EEG signals. However more work required to be conducted to interface with the machine and human. And also, we have observed that very few imagined data sets are available for BCI applications but still need to be adequately deployed in BCI applications due to a lack of data. Furthermore, all the available EEG data sets pertain to normal and healthy subjects only, particularly in decoding imagined speech. Any BCI model developed using the available data set will be helpful to people who have brain disorders while they are growing up or who are injured accidentally or due to illness. But may not be helpful to disabled people by birth itself.

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